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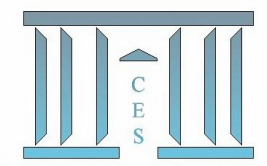

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An Emerging Market Financial Conditions Index: A VAR Approach*

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Abstract

The recent financial crisis has heightened the interest in the impact of financial sector developments on the macroeconomic condition of countries. By employing a rolling-window Vector Auto-Regressive method based on monthly data for a time span between January 2001 and March 2013, this article sets up a comprehensive financial conditions index for a set of major emerging countries. The index sheds light on the various triggers of financial crises during this period and captures both domestic developments as well as global spillover effects. Index dynamics exhibit an overall abrupt slowdown due to the 2007-2008 Financial Crisis, precipitated primarily through a global liquidity squeeze and overall financial sector strain. In some countries, rising volatility of financial conditions thereafter has substantially been sparked by nominal effective exchange rate movements. Tested on its forecasting applicability, the inclusion of macroeconomic and financial variables enables the index to also perform well as a leading indicator for business cycles.

JEL: C32, C53, E44, F42
Keywords: Emerging Markets, Financial Conditions Index, VAR, Leading Indicator

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1 Introduction

The financial crisis in 2007-2008 has sparked renewed interest in the impact of financial sector developments on the macroeconomic conditions of countries. Crisis fallout has molded the global financial system dysfunctional resulting in a striking interruption of macro-financial linkages. Eventually, this has led to an impediment to economic growth of varying degrees and once again has evidenced how severe the influence of financial market strain on the real economy may become. With the recent crisis wreaking havoc on economic output, policymakers have increasingly sought to disentangle propagation channels of financial stress and turned towards operational tools which hitherto aimed at monitoring the evolution of monetary policy. Yet, monetary policy as a means to smoothen brittle points of business cycles does not always lead to the desired outcome, particularly in times of an impaired financial system.

This article constructs a financial conditions index (FCI) composed of financial and macroeconomic variables as a natural and consistent extension to aforementioned policy-making devices. Its design allows not only proctoring monetary policy but also for an assessment of the evolvement of overall financial conditions and their impact on the real economy. Thus by construction, the FCI constitutes a leading indicator for business cycle evolvement whose efficacy and applicability will be tested in the upcoming sections. The index allows further for a dissection of triggers of and driving forces behind global and regional spillovers of economic developments covering a period of January 2001 to March 2013.

Instead of focusing on advanced economies, the FCI approaches macro-financial linkages of major emerging countries, namely Brazil, China, India, Russia, and South Africa (BRICS hereafter). These countries exhibit significant differences in their economic structure as well as their conduct of monetary policy and hence serve as a natural litmus test for a broader application of our index. Moreover, all sample countries are setting economic tone in their respective region and may thus be regarded as a point of reference for neighbouring economies in terms of policy making and economic dependence.

By using a vector auto-regressive approach for its construction, we calculate the impulse response of GDP to a shock on each financial variable included in the index. As in Guichard and Turner (2008), Guichard et al. (2009), and Shinkai and Kohsaka (2010), the sum of the responses on a given time horizon constitutes the FCI. However, compared to the previously mentioned papers, this article features a novelty in form of an innovative five-year rolling-window regression technique. Consequently, this method permits to obtain time-varying weights of each financial variable in the FCI. An aggregation of index weights allows for capturing domestic changes in economic structure, as for example the adoption of an inflation targeting framework or a more flexible exchange rate regime, as well as international financial disruption. To our knowledge, this paper is the first that uses data on a monthly frequency when considering the BRICS.

The calculated indexes exhibit the expected abrupt slowdown in each country caused by the stark global economic contraction in the 2007-2008 period. Time-varying sub-indexes confirm the different driving factors behind crisis emergence throughout our sample. Moreover, the corresponding graphical representation of each variable share in the FCI validates the usefulness of the rolling-window regressions since individual weights seem to vary over time. As evidenced by the weight contributions, volatility in financial conditions in pre- and post-crisis periods are primarily provoked by global liquidity provision. Although on the one hand a policy measure that is improving economic sentiment up to the eve of the crisis, it leads on the other to more accentuated movements in the indexes afterwards.

In terms of robustness, the correlation of our FCIs with GDP seems to be higher compared to previous papers by Swiston (2008), Beaton et al. (2009), and Lu et al. (2013). This strong performance is further confirmed by additional robustness tests such as Granger causality tests, out-of-sample forecasting exercises, and the Diebold and Mariano test. Moreover, our index seems to outperform the Leading

Indicator created by the Organization of Economic Co-operation and Development (OECD) in terms of GDP forecasting ability over a long term horizon.

The paper is structured as follows: The subsequent section clarifies the difference between the two kinds of indexes generally used in the literature, the financial stress index and the financial conditions index, the latter being employed here for the purpose of this article. Moreover, it covers hitherto research on the topic and further motivates the applied VAR methodology. Section III explains the model in detail and states the variables retained for the FCI analysis. Section IV embarks upon an interpretation of results and Section V evaluates the index by performing several robustness and precision checks. Eventually, Section VI concludes.

2 Index Literature

Financial crises episodes usually can be attributed to specific triggering events. However, a more rigorous analysis of particular crises across different countries requires more systemic and quantified information than just a root cause. Even though crises may originate in different market segments and linger through varying channels, the degree of persistence and its unique evolution within each country translate into a variety of impacts on the real economy, limited either to the domestic level or across national borders. Thus, being able to quantify levels of financial stress does not only create the capability to react to future developments exhibiting similar stress characteristics, but also allows for better comparison and a more clear-cut classification of historic events in terms of length and duration.

2.1 Financial Stress Index vs Financial Conditions Index

Addressing these issues is a relatively new segment in economic literature. The majority of approaches to measure financial market stress, and covering primarily developed countries, has only since recently appeared, together with a gradual abatement of the global financial turmoil. The field has attracted attention in both academia as well as policy making and features most prominently, among others, the IMF, and several central banks, such as the ECB, Kansas City or St. Louis Fed (see, e.g. Cardarelli et al. (2011), Hakkio and Keeton (2009), Kliesen and Smith (2010)).

A common method for measurement are the so-called "Financial Stress Indexes" (FSIs) or "Financial Condition Indexes" (FCIs), where financial strain is generally quantified over a broad set of different product or market categories. By aggregating these distinct elements into a time series of fluctuating values, the indices allow to express the degree of financial stress in the economy and the respective likelihood of a crisis occurrence.

The main difference between FSIs and FCIs lies in a more reduced set of financial variables employed in the FSI, i.e. primarily prices measures, whereas the list of variables included in the latter tends to encompass a richer variety ranging from mere prices to macroeconomic indicators (Kliesen et al.(2012))[1].

However, this proximity with regard to variables employed creates certain forms of overlappings between both index forms, which in addition often exhibit also similar construction patterns. Consequently, interpretation and application are determined by individual conception and the distinctive sets of variables applied require some sensitivity for an efficient use of FCI and FSI as both serve two different purposes.

[1] FSIs include mainly price variables from e.g. traded asset classes or stock indices, in order to mirror as accurate as possible the level of activity within the financial sector. FCIs in turn use apart from price measures variables of demand and supply for financial instruments relevant for economic activity, i.e. both quantity and economic indicators.

By including primarily financial variables, indexes for financial stress can be interpreted as to exhibit the level of fragility in a certain financial market under scrutiny and hence are able 'to distill the information about financial market functioning' (Carlson et al. 2012: 13). Proper functioning is strongly dependent on a smooth working of institutions active in the market and a foreseeable behaviour of all agents involved. In case of disruption market malfunctioning, resulting in different degrees of financial stress, can therefore take on a variety of forms.

According to Hakkio and Keeton (2009) as well as Sandahl et al. (2011), financial stress may be related to varying degrees of impaired interbank activities, financial intermediation, and increasing asymmetric information on asset pricing, what in turn triggers unusual market participant behaviour consisting in flights to quality and liquidity. Balakrishnan et al. (2009) do not emphasize any specific definition but rather identify financial stress roughly as periods of financial turmoil, exchange market pressure through e.g. a depletion of reserves or rapid depreciation, or high stock return volatility. Apart from a more unidimensional approach to the financial sector, potential spillover effects among single market segments are treated in indexes covering the concept of systemic financial stress[2], an event, where the entire financial system is endangered and may negatively affect economic growth and welfare.

Notwithstanding its sophistication, the concept of financial stress and its representation through a FSI is at times considerably abstract, because it is not related to any other quantifiable measure. A comparison is only possible relative to itself or to other stress indexes, provided, as emphasized above, that the skillful user is aware of its construction, the variables employed and the ultimate purpose it serves.

In contrast to its financial stress counterpart, the FCI embraces a more global picture and relates financial strain to the broader economic situation. A FCI tries to look at transmission channels of financial activity, epitomized by fluctuations in financial variables, to the real economy and has by design as its main application the assessment of macroeconomic implications derived from developments in the financial sector. Some indexes, produced for example by Hatzius et al. (2010) or Brave and Butters (2012), try to exploit this distinct characteristic and attempt to forecast economic activity in terms of economic growth by measuring the impact of exogenous variations in financial conditions.

The emphasis of this article therefore rests on the interplay between developments in the financial sector and their respective significance for the prevailing economic situation at a certain point in time. Due to the apparent much better suitability of a FCI for our task, we follow this strategy and draw with the construction of an emerging countries index to some extent on the accomplishments already achieved in the relevant literature.

After having briefly outlined the aim of this article as well as particularities in index composition and application, the next section provides a detailed overview of methodologies and construction techniques used up to now and examines their individual advantages as well as weaknesses.

2.2 Methodologies for Index Construction

2.2.1 Orthodox Measures

The literature on the construction of financial indexes can roughly be divided into two strands, a rather orthodox approach and an econometrically more advanced strategy that makes inroads into the vector autoregressive literature. The former is largely based on Illing and Liu's (2006) index for Canada, where stress events are extracted from a survey among central bank officials, which are then compared to an estimated index. Among a variety of employed aggregation methods the credit-aggregate weighting

[2]For a more in-depth treatment of systemic stress refer to Hollo et al. (2012), Lo Duca and Peltonen (2009) and Louzis and Vouldis (2011).

technique is considered to be the most appropriate for combining the subindex stress variables into an aggregate. Predetermined stress events though, as in the case of the survey, may limit the explanatory power of the index due to a selection bias and can impede proper technical adjustments of the index to financial strain outside the central bank's perspective.

Another often mentioned index with direct methodological reference to the previous one is the IMF FSI from Cardarelli et al. (2011). With the variance weights simply averaged over three stress subindices that are roughly related to banking, securities, and foreign exchange, the authors expand their analysis to a dataset of 17 advanced countries with uniform time series for each country. The same methodological approach is used for stress indicators on emerging markets by Balakrishnan et al. (2009 and 2011), and Park and Mercado (2013), in an attempt to evaluate financial contagion transmitted from advanced to developing countries. Yet according to our opinion, these indexes suffer from a major drawback. Apart from the rather reduced set of variables to choose from due to their cross-country nature, the equal weighting of subindex dimensions attaches a constraint of rigidity to the indexes. Consequently, dynamic developments in domestic financial markets cannot properly be taken into account. The same holds for the index on financial development in emerging markets constructed by Dorucci et al. (2009), where equal weighting among subindices and therein contained variables is, according to the authors, considered to be tantamount to equal relevance of represented financial market segments.

A more sophisticated and quite recent approach comes from Hollo et al. (2012), who created "CISS" - a composite indicator for systemic financial stress for euro area data. Their indicator entails a denouement compared to the hitherto seen ones, in that the aggregation of the five subindices, with individual stress measures arithmetically averaged, draws on portfolio-theoretical elements. They consist in time-varying cross-correlations among the subindices which are estimated through GARCH models for emphasizing the systemic nature of the crisis index. Normalized stress measures for index aggregation, however, imply according to standard literature[3] a Gaussian distribution of the variables. Normalization of data for the CISS is therefore based on the "Cleveland Financial Stress Index" developed by Oet et al. (2011), who transform the values of each series into the corresponding value of their empirical cumulative distribution function. This conceptual foundation also serves as point of departure for a paper by Louzis and Vouldis (2012), who construct an aggregated stress indicator for Greece by relying on principal component analysis (PCA) for their subdomains. This method may be useful if the initial dataset is considerably large, as e.g. in Angelopoulou et al. (2013) for a very recent index on the euro area with emphasis on the impact of monetary policy. PCA allows to identify the main drivers for index volatility in order to suppress redundancy among a large array of variables without imposing a prior structural framework on the estimated model.

2.2.2 VAR Models

Advantages of VAR Methodology Another quantitative strand of literature has been devoted to analyzing financial conditions through the technique of Vector Auto-Regressions (VAR). Provided that evolving economic environments are concerned, this method offers several reasons for its application to index construction. By taking endogeneity between variables into account, VARs allow for a dynamic capture of responses among included variables, lagged responsiveness of these variables as well as an implementation of a time-varying weighting mechanism.

Conventional models (e.g. Mayes and Viren (2001)), that are based on aggregate demand functions relating output gaps to interest rates and exchange rates, often consider financial variables as mere exogenous factors in the relation to each other and to macroeconomic regressands. This implies that mutual

[3] A more detailed overview on techniques described in this paragraph can be found e.g. in the OECD Handbook for Composite Indexes (2008).

influence and causal effects of movements among dependent and independent variables cannot be singled out. Early monetary policy indexes, however, have recognized these issues and accounted for direct and indirect effects of interest rates on both other explanatory variables and the independent variable GDP. Thus, it still remains a widely used method for forecasting and capturing of structural macroeconomic effects that come from monetary shocks (e.g. Christiano et al. (1999) or Justinano et al. (2009)). As argued by Gauthier et al. (2004), VARs are particularly suited to reduce identification problems of variable impacts on the regressand and help to alleviate a potential estimation bias as all variables are endogenous.

Apart from a favourable treatment of endogeneity, a VAR becomes indispensable for index aggregation by substituting an often predetermined weighting of subindices for a more flexible method that is responsive to dynamics in the macroeconomic environment. The employment of Impulse-Response Functions (IRFs) allows for such a weight determination of each subindex through estimating the impact of shocks on both the response variable and other regressors. Moreover, in contrast to previously mentioned GARCH models, VARs permit the application of time-varying weighting parameters without explicit Gaussian assumptions about the underlying data distribution. Ultimately, time-varying and dynamic weighting thus captures to a very high degree potential feedback effects among regressors in the model.

Cholesky Decomposition and Ordering of Variables However, apart from the previously outlined advantages over other methods, also a VAR requires some technical susceptibility. The main challenge of its application to index construction comes with models that are based on economic theory, i.e. structural VARs (SVARs). Compared to a reduced form, they often require an ordering of regressors according to their intrinsic relationship with each other and the degree of alleged mutual impact. Ordering variables in one way or another, however, influences the Cholesky decomposition of the variance-covariance matrix and subsequently the computation of orthogonal IRFs through 'imposing a recursive structure on the contemporary relationships of the variables' (Ronayne 2011: 4). As a consequence, potential misalignment may negatively bias the above mentioned weighting process. Nonetheless, citing Wong (2008: 3), '[...] the selection of ordering in Cholesky decomposition is generally ad hoc, and convincing identifying assumptions are hard to come by'.

Different authors find varying answers to short-term ordering and restriction issues of SVARs. Goodhart and Hofmann (2001), for example, construct an FCI for the G7 countries with the aim to assess the impact of asset price information on aggregate demand conditions and on monetary policy transmission. Starting with an aggregate demand function consisting of a backward-looking Philipps Curve and a backward-looking IS demand curve both separately estimated by OLS, the weights for the FCI are derived from the coefficients. For the alternative VAR approach, a variable ordering with respect to decreasing sluggishness has been chosen for the Cholesky. It is thus the degree of responsiveness to shocks in other variables what determines the position of a variable, moving from more exogenous macroeconomic variables to financial ones. Comparing the initial OLS weights to those collected from the restricted VAR, results exhibit a similarity in weights yielded from both models. Analogously Swiston (2008), by predicting US GDP growth through a FCI, orders his regressors according to their relative stickiness in response to changes in other variables.

Also Shinkai and Kohsaka (2010) in a FCI for Japan arrange their variables in decreasing order with respect to the degree of exogeneity. As such, the oil price is placed in front, followed by the financial variables. All other real economic regressors are positioned at the end for being considered the most endogenous. By following Pesaran and Shin (1998) and Gauthier et al. (2004), Guichard and Turner (2008) as well as Osorio et al. (2011) use for their US and respectively Asia FCIs generalized IRFs to avoid the impact of a pre-ordering of variables on estimation results. The average lag lies between four to six quarters as they try to take into account relevant lagged effects of monetary policy. A more comprehensive approach has been pursued by Guichard et al. in their 2009 paper, where the targeted

geographical area has been augmented to further include the euro area, Japan, and the United Kingdom. The existing US FCI has been taken as the reference index, and the inclusion of other countries is accomplished through judgemental calibration instead of individual VAR estimation in order to avoid counter-intuitive cross-country comparisons.

Following the tradition of above mentioned previous work, Beaton et al. (2009) estimate via two FCIs the contribution of financial shocks on quarterly US GDP growth. The first index, based on orthogonalized IRFs from a structural vector-error correction model, includes financial variables capturing the price and quantity channels of credit constraints and significantly influence GDP growth. The second FCI predicates on a large macroeconomic model from the Bank of Canada with similar financial variables, the MUSE (Gosselin and Lalonde (2005)). Variables are again ordered with respect to their relative exogeneity and a Cholesky decomposition is performed for the IRFs. Concluding, both indices indicate a tremendous impact of credit constraint on economic growth in the period under scrutiny.

As a result of the methodological overview above, a VAR model featuring a short-term Cholesky decomposition for variable ordering will be used in the construction of our index. The next section presents a detailed outline of the employed estimation technique and the selection process for variables included.

3 Model, Decomposition, and Data

3.1 VAR Model

Following Sims (1980), the model of order p is written:

$$y_t = \alpha + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \epsilon_t, t = 1, ..., T \tag{1}$$

With $y_t = (y_{1t}, ..., y_{nt})'$, $\beta_i = (\beta_1, ..., \beta_p)$, α, ϵ_t being respectively a p-column vector of the dependent variables, a $n - by - n$ matrix of VAR coefficients, the intercepts and a p-column vector of error terms, independent to lagged values of y_t such that $\epsilon_t \sim N(0, \Sigma)$ where Σ represents the error covariance matrix and is positive definite.

3.2 Cholesky Decomposition and Data

We apply a Cholesky decomposition as in Swiston (2008), and Shinkai and Kohsaka (2010) on seasonally adjusted data with a monthly frequency. This has the effect that a variable ordered earlier has an immediate impact on the following variables, while a variable ordered later exerts only a lagged influence on the previous variables. Thus we rank the variables from the most to the least exogenous. External variables are introduced with three lags to account for their delayed response. Data is available from 1995M01 on, for Russia, however, variable series commence one year later, in 1996.[4] Unfortunately, data availability for the period under scrutiny precludes other developing countries from being tested.

$$y_t = \begin{bmatrix} \text{World production} \\ \text{External financial variables} \\ \text{Domestic GDP} \\ \text{Domestic financial variables} \end{bmatrix}$$

All variables included later on are transformed in logarithms – except for interest rates – and are first differenced for stationarity reasons. The world production series remains the exception due to HP filtering

[4]Data is obtained from Reuters *Datastream* except for the banking sector variable DS Bank where data comes from *Bankscope*

(Hodrick-Prescott-Filter). Samples vary according to data availability and are specified in the Appendix with data sources and exact definitions of sample size (Table 7 & 8), descriptive statistics (Table 9) and the respective Augmented Dickey-Fuller (ADF) tests (Table 10), as well as correlations among variables (Table 11). The correlations show that the VAR methodology can be applied without encountering issues of redundancy.

We test a wide range of external financial variables commonly used in the literature:

- Emerging Market Bond Index (EMBI)[5] to measure the risk aversion of a given country
- Global stock exchange indexes to measure the global level of risk. We test several stock indexes for each country:
  - S&P500 for the US stock exchange
  - FTSE100 for the London stock exchange
  - Hang Seng for the Hong Kong stock exchange
  - SGX for the Singaporian stock exchange
  - Tokyo stock exchange
- US Monetary Policy:
  - TED spread is the difference between LIBOR and the US Treasury Bills on a three-month time horizon. It measures the global liquidity level in the interbank market and the projected path of US monetary policy. Owing to its composition, the TED spread is also an indicator for a flight to safety, a flight to liquidity, as well as rising information asymmetries in the market.
  - US Federal Funds Rate (US FFR)
- VIX of S&P500 to measure the appetite for risk of international investors

And a wide range of domestic financial variables:

- Credit
  - To all sectors
  - To private sector
- Domestic stock exchange indexes: first differenced or rolling window volatility
- Domestic bank stock indexes: stock index performance of the four major banks in each country, first differenced or rolling window volatility
- Exchange Rate:
  - Nominal Effective Exchange Rate (NEER): first differenced or rolling window volatility
  - Exchange Market Pressure Index as in Balakrishnan et al. (2009)

$$EMPI_{i,t} = \frac{\Delta e_{i,t} - \mu_{i,\Delta e}}{\sigma_{i,\Delta e}} + \frac{\Delta RES_{i,t} - \mu_{i,\Delta RES}}{\sigma_{i,\Delta RES}} \tag{2}$$

with e and RES that represent respectively the NEER and the total amount of reserves, with the mean μ and the standard deviation σ of a change thereof. An increase of the NEER (appreciation) or an increase in the total amount of reserves means more pressure of the foreign exchange market.

[5] *Emerging Market Bond Index Plus*, tracking returns for actively traded external debt instruments such as Brady bonds, Eurobonds, or traded loans issues by sovereign entities (J.P. Morgan, 1999)

- Domestic monetary policy
  - Domestic interbank interest rate
  - Money supply M1
  - Reserve requirements
  - Foreign reserves

3.3 Methodology

We decide to follow roughly a two-step approach proposed by Swiston (2008) for distilling the most significant financial variables from the list above. First we run a restrictive VAR with the basic variables world production and domestic GDP as well as one financial variable, where the response of GDP to the individual financial variable is estimated. Eventually, we retain a financial variable if it is significant and if the parameters associated with domestic GDP have the expected sign.
Though reminiscent of a step-up approach as presented in Dunnett and Tamhane (1992), our variable selection procedure differs in the way that variables are tested for significance on a one-by-one basis and are not gradually added and retained if their presence improves overall explanatory power.

A methodological innovation consists in a rolling window of five years based on the underlying assumption that regression parameters may vary within every window corresponding to changing fundamentals in both the economy and the financial sector[6]. Since the model requires stationarity, we lose one year for variable transformation and the first regression thus runs for the period 1996M01 - 2001M01 (1997M01 - 2002M01 for Russia). As a consequence, the index commences for all countries with January 2001, for Russia again as the exception with 2002M01. The window of regression is shifted by month from January 2001 (January 2002 for Russia) to March 2013 – in the case of India and South Africa up to July 2012 and December 2012 respectively.

Subsequently, regressions are performed in a more global model by using the same procedure for each country containing world production, domestic real GDP, and the from step one retained financial variables. For each shifting regression window lags are allowed to vary from one to five with a tighter measure in periods of crisis. The choice of lag numbers is determined through the AIC, BIC, and SBIC information criteria.

The index is computed through IRFs[7] referring to Guichard and Turner (2008), Guichard et al. (2009), and Shinkai and Kohsaka (2010). Generally speaking, IRFs measure the reaction of a dependent variable to a simulated shock on other variables of the system. In our specification, we calculate the response of GDP to a simulated shock on each financial variable for a given time horizon p. The FCI for a given country at time t with m retained financial variables therefore is:

$$FCI_t = \sum_{j=1}^{m} \left(\frac{\sum_{i=0}^{j} w_i^j v_{t-i}^j}{p} \right) \tag{3}$$

The equation above reflects the sum of the means of p - time horizon IRFs to a simulated shock on each financial variable j , i.e. w_i^j and v_{t-i}^j represent respectively the i^{th} months lagged impulse response of domestic GDP to a shock of a financial variable j and a structural shock of the latter. Notice that the time horizon p is set to eight. This implies that we calculate the mean of the responses on eight months. However, the index does not change significantly if we reduce or increase the time horizon[8].

[6] Different window widths have been tested, the selected 5-year window, however, showed the best results.

[7] The inclusion of IRF graphics do not add to further clarity and are thus not explicitly presented in the paper. However, they are available upon request to the authors.

[8] Summed-up time horizons ranging from 6 to 12 periods have been tested. Whereas the six-period time horizon constitutes the peak response of domestic production to a financial variable shock, further afield horizons up to 12 periods turn out to be non-significant.

4 Results and Interpretations

The retained variables are ordered as in Table 1. A change in order either within the foreign or the domestic variable group does not lead to significant differences in results obtained. The small number of variables kept for each country is a direct result of the method employed as the variables retained deliver the best results among other alternatives for every country in the sample. The composition of domestic and external variable sets may encounter minor adjustments in justified cases, e.g. the domestic stock index for Russia. This rigorous structure of the individual indexes facilitates a comparison of financial conditions among the different countries.

Table 1: Country Variables Retained

Brazil	*China*	*India*
World Production	World Production	World Production
TED spread	TED spread	TED spread
S&P500	Hong Kong stock exchange	Hong Kong stock exchange
Domestic Production	Domestic Production	Domestic Production
NEER	NEER	NEER
Domestic interbank interest rate	Money supply	Money supply

Russia	*South Africa*
World Production	World Production
TED spread	TED spread
Domestic Production	S&P500
NEER	Domestic Production
Domestic interbank interest rate	NEER
Domestic stock exchange	Domestic interbank interest rate

What do FCIs say about growth? Through our previously mentioned construction method, the FCIs sum up the aggregated reaction of domestic GDP to shocks to financial variables. It may therefore be argued that the indexes account for quite some variation in domestic output and thus the business cycle.

As an initial check for significance and applicability as a potential leading indicator, we follow Swiston (2008), and Beaton et al. (2009) and calculate the correlation between the FCI and domestic real GDP. The results throughout our country sample exhibit high significance in correlations with values ranging from approximately 75 percent for Russia up to 86 percent for China. Results are presented in the following table. Hence, our correlations seem to be higher than those of previous papers by Swiston (2008), Beaton et al. (2009), and Lu et al. (2013), which yield respectively 0.68, 0.52 and 0.6, and for the latter 0.56 depending on the methodology applied. This is also in line with Stock and Watson (2003) who assert that multivariable forecasts exceed those of any individual financial component.

Table 2: FCI Correlations with GDP

Brazil	*China*	*India*	*Russia*	*South Africa*
0.7969	0.8606	0.8436	0.7482	0.7737

(Source: Authors' calculations)

In the following Figure 1, we plot the FCIs with standard deviation boundaries for our five countries transformed by a quarterly moving average what leads to slightly smoother graphs and facilitates interpretation. The area in the graphs above the zero normalcy line represents periods of looser financial

conditions whereas the area underneath indicates tighter conditions. When the index exceeds the the range of one standard deviation financial stress is classified as severe [9]. Hatzius et al. (2010), and Hakkio and Keeton (2009) also suggest that if the index is outside of the set range channels for the transmission of monetary policy are susceptible to impairment due to financial market frictions. As presented below, the consequences of the 2008 financial crisis in terms of financial conditions for the five countries, and other regional crisis events likewise, can easily be identified and contrasted in terms of duration and depth.

Interpretation of FCIs The following paragraphs split the interpretation of the above shown FCI graphs into three periods, a pre-crisis period, the crisis years, and an after-crisis period that emphasizes the most recent developments.

Pre-crisis Period (2001 - mid 2008)

For our emerging countries, the period before the 2007-2008 financial crisis can be roughly divided into two halfs: The first half from 2001 to around 2004 is characterized by overall rather volatile financial conditions which may be partly attributed to the fallout of a burst of the information technology bubble during 1999-2001, letting global stock indices descend. Moreover, different countries have either been hit by domestic crises or have seen spillovers on their economies from different regional events. For example, the fall in financial conditions in South Africa in 2001 can be attributed to the then Rand crisis, a sudden erosion in the South African currency. Brazil's decline of its FCI in mid 2003 may well be linked to spillovers from the Argentinian crisis which had a negative effect on the whole region and was particularly hitting economically well-linked and integrated neighbours.

The second half covers approximately the years from 2005 up to the onset of the crisis in 2008 and is characterized by an overall tranquility and a rather moderate comportment of financial conditions (Meirelles (2009)). This is in particular discernible for Brazil, China, and Russia. With regard to India and South Africa, a general upward movement in the FCI indicating an improvement of overall conditions can be experienced. This upswing may correspond to a then unprecedented global liquidity provision through central banks. Extended liquidity has to a large extent been absorbed by international stock markets, something that is furthermore reflected by the high contribution of stock indexes (S&P 500 and Hong Kong Hang Seng) to the country FCIs, displayed in subsequent variance decomposition graphs.

[9] The selected cutoff of one standard deviation is a compromise with respect to utilised thresholds in the literature.

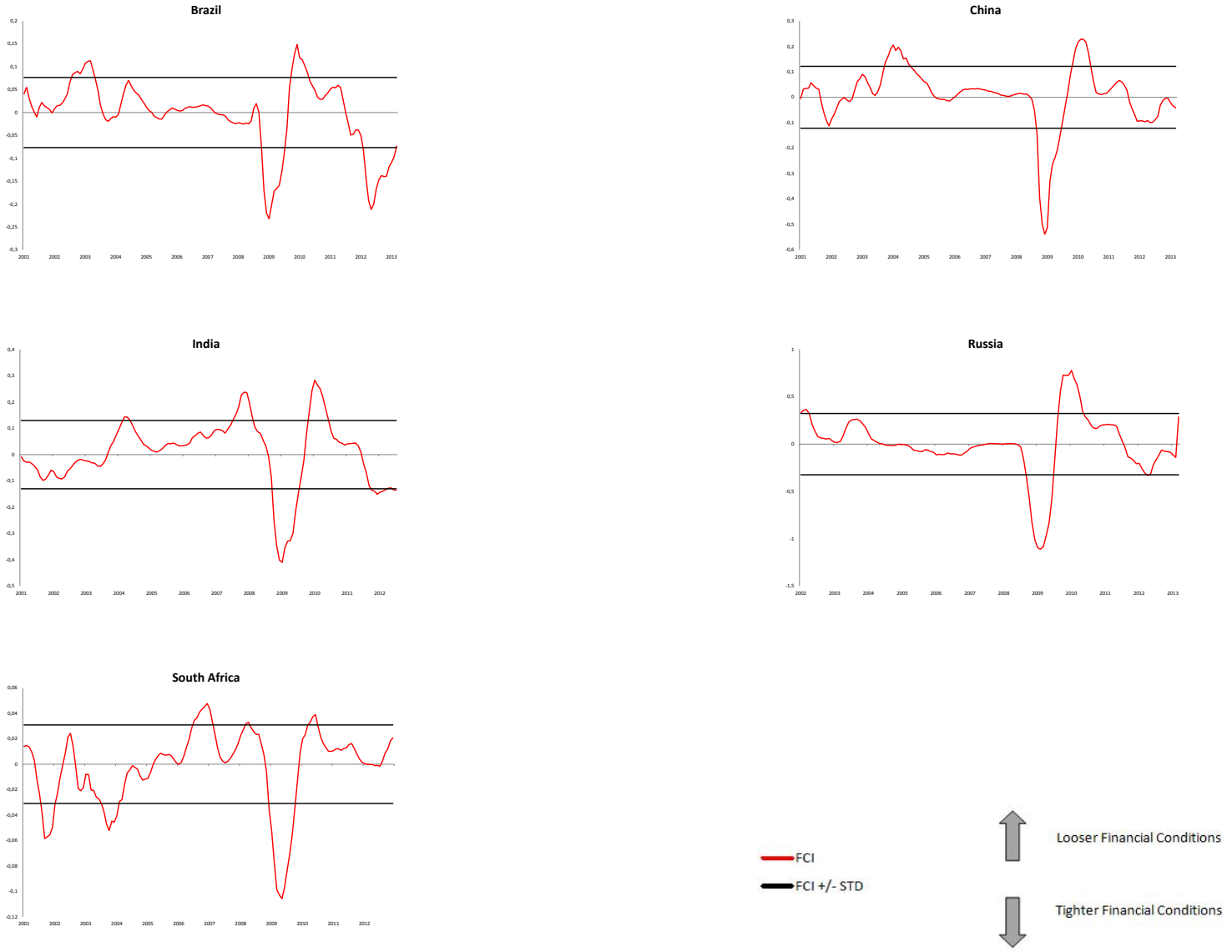

Figure 1: Financial Condition Indexes (Source: Authors' calculations)

Table 3: Current Central Banks' Objectives, Currency Regimes and Important Economic Events

Brazilian objectives:	to ensure the currency's purchasing power and a solid and efficient financial system.
January 15, 1999:	the Brazilian currency is allowed to float.
June 1999:	implementation of an IT framework.
	Three periods of devaluation took place and were considered in a test for the IT framework:
	48.9% in 1999, 18.5% in 2001 and 53.2% in 2002.
1999-2001:	burst of the information technology bubble.
2002-2003:	South American Economic Crisis.
2007-2008:	Global Financial Crisis in the US and Europe, originating in a closure of funds by BNP Paribas
	and the liquidity crisis of Northern Rock in mid-2007; spillovers to the rest of the world approximately one year later.
Chinese objectives:	to maintain the stability of the value of the currency and thereby promote economic growth.
After the Asian crisis of 1997-1998:	reduction of the ER band in order to prevent huge currency depreciations.
2005:	adoption of a managed floating ER regime based on market supply and demand with reference to a basket of currencies.
Up to the end of 2007:	the ER appreciated by 11% compared to 2005 and 26.6% to 1994.
2007-2008:	Global Financial Crisis with spillover to China roughly one year later.
End-2007-mid-June 2010:	currency peg regime.
Mid-June 2010:	monetary authorities again starts to increase the flexibility of the renminbi.
Indian objectives:	to maintain price stability, and ensure the adequate flow of credit to the productive sectors of the economy to support
	economic growth and financial stability.
August 1998 up to March 2004:	after the Asian crisis, adoption of a currency peg regime with sterilized interventions.
1998-today:	multiple indicator approach for monetary policy.
	It involves interest rates, CPI rate, money supply, credit, ER, trade, capital flows, fiscal position and output.
March 2004:	monetary authorities decide to introduce greater flexibility in the fluctuations of their currency.
	However, the central bank has remained evasive about its operations to contain liquidity and ER volatility.
2007-2008:	Global Financial Crisis with spillover to India roughly one year later.
Russian objectives:	to protect the ruble and ensure its stability,
	promote the development of and strengthen the Russian banking system,
	and ensure the efficient and uninterrupted functioning of the payment system.
2000-2004:	currency board regime vis-a-vis a bundle of two currencies: 55% dollar and 45% euro.
2004-2007:	middle approach to get gradual appreciation of ER with acceptable levels of CPI and liquidity.
Since the last crisis:	the central bank has moved toward the adoption of an IT regime with more flexibility in the ER regime.
2007-2008:	Global Financial Crisis with spillover to Russia roughly one year later.
South African objectives:	to achieve and maintain price stability in the interest of balanced and sustainable economic growth
	and, together with other institutions, ensure financial stability.
1999-2001:	burst of the information technology bubble.
February 2000:	adoption of an IT framework.
September 1-31, 2001:	the currency devalues by 42% against the US dollar.
2007-2008:	Global Financial Crisis with spillover to South Africa roughly one year later.

The Crisis

In advanced countries, the crisis already exerted some impact on financial sector developments directly after the closure of funds by BNP Paribas in August 2007 and the liquidity crisis of Northern Rock one month later. With regard to major emerging countries, the shock arrived with a time lag of roughly one year. Nonetheless, the crisis hit hard throughout the entire sample of countries. With Russia and China seeing their indexes plummeting by more than three standard deviations, both countries were the most affected among the BRICS. Yet, financial conditions rebounced uniformly fast after having reached the trough around half a year after the crisis onset.

After-crisis Period From Early 2010 Onwards

Emerging countries experienced a rather quick recovery from the crisis with financial conditions already peaking in the early months of 2010. This rapid improvement of financial conditions was primarily caused by the concerted action of central banks to ease monetary conditions and to provide global markets with liquidity. Capital flows to emerging markets resumed, consisting primarily of portfolio equity and fixed-income investments (IMF 2010). Yet, recovery soon lost its pace and the FCIs of Brazil and India in particular came under pressure. An increasing tightening of conditions was therefore visible owing primarily to a considerable depreciation of the Real and the Rupia precipitated by a deteriorating economic outlook at home. South Africa and China in contrast exhibit more moderate movements.

Variations in Subindex Shares

In order to facilitate a better identification of sources of stress in financial conditions, we plot below in Figure 3 the relative contribution of each variable to the index for the months January, May, and September in every year throughout our observation period. The share of each financial variable at each point in time is determined not only by its shock but also by its estimated impact on growth, i.e. its weight in the FCI.

As it can be discerned, shares vary considerably over time. This confirms our hypothesis that relationships between variables are not constant throughout the whole period. In the cases of China, India, and Russia, domestic and supra-regional stock exchanges (seen as a proxy for global liquidity) feature prominently as a main driving force behind financial condition movements. For example, Figure 2 represents the evolution of the weight of each subindex in the FCI[10] over time for China. It shows that the Hong Kong stock exchange is the main driver of the FCI, except for the period where more flexibility in the NEER were introduced by the central bank from 2005 up to the end of 2007 (Table 3).

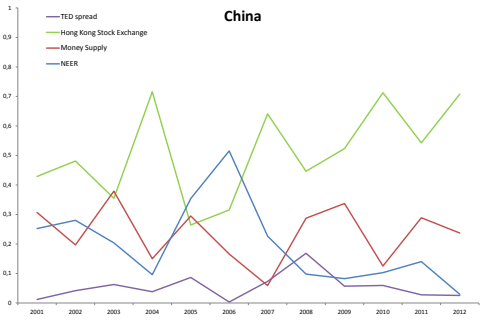

Figure 2: Variations in Subindex Shares (Source: Authors' calculations)

[10]The sum of subindex contributions equals 1 for each month.

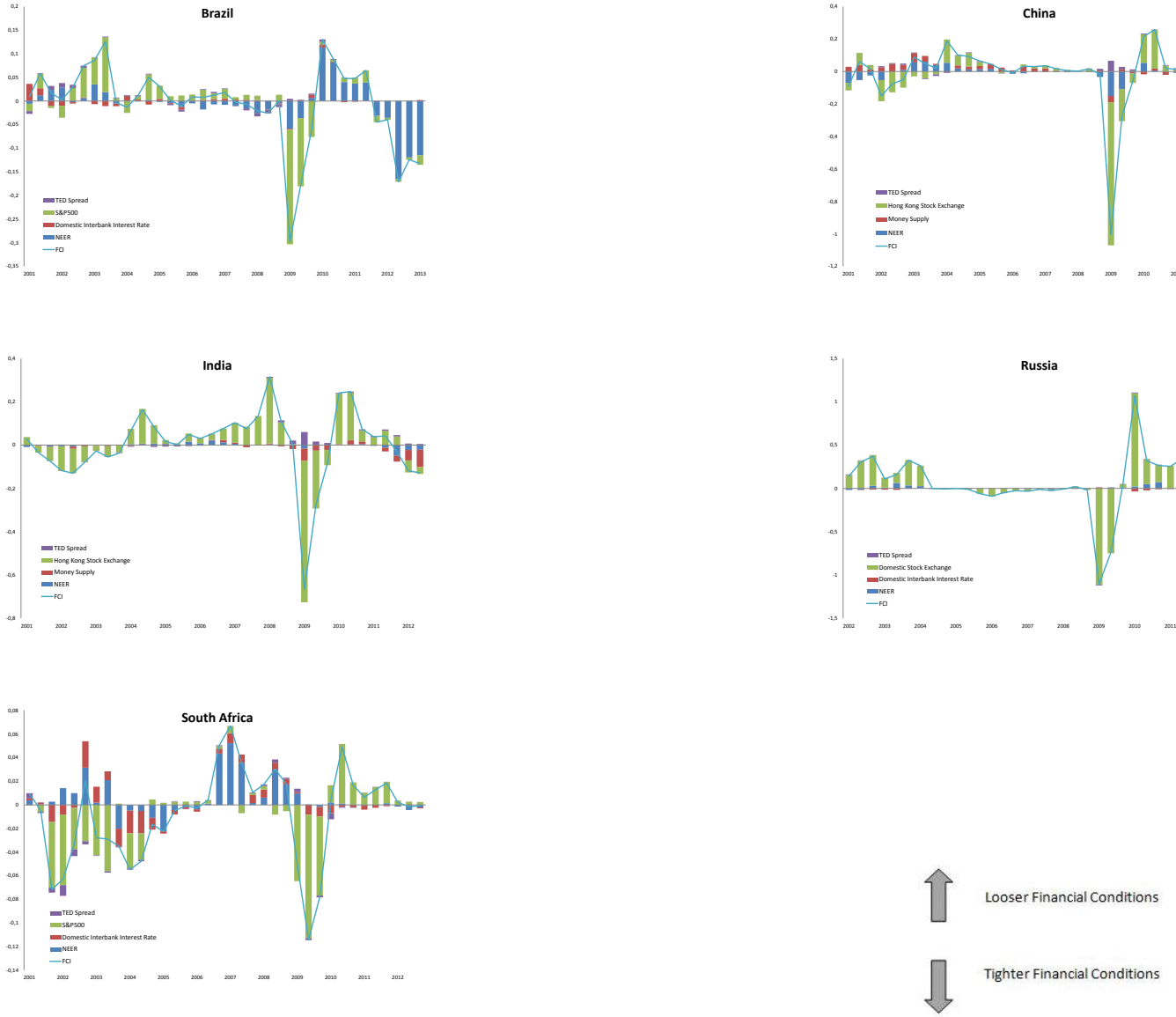

Figure 3: Subindex Contributions (Source: Authors' calculations)

A similar development can be discovered for Brazil prior to 2007 as well as during the 2008 financial crisis and still holds currently for South Africa (Figure 4). Furthermore, the graphs confirm our analysis from above as the present poor financial conditions in Brazil are mostly associated with a previously mentioned depreciation of the Brazilian currency as for example in Nelson (2013). We further note that the share of the Brazilian exchange rate has continuously increased since 2004 – except during the latest financial turmoil – whereas the domestic interbank interest rate has played an increasing role in the South African FCI up to the 2008 financial crisis.

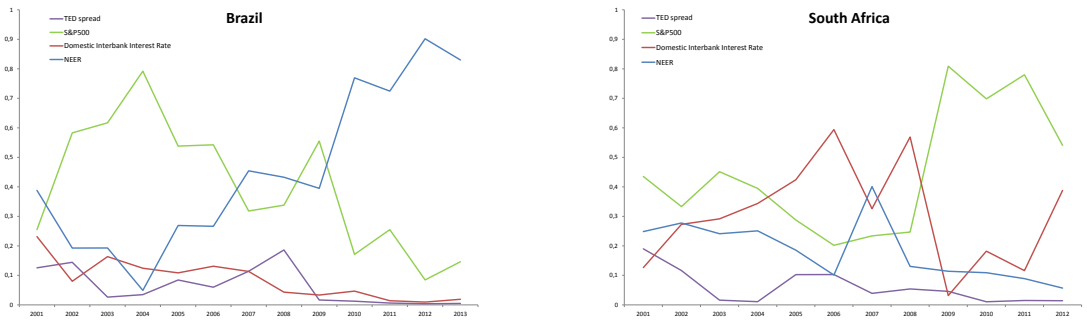

Figure 4: Variations in Subindex Shares (Source: Authors' calculations)

Moreover, even if the TED spread as a 'proxy for US liquidity pressure' (Fratzscher and Chudik (2011: 17)) plays a significant role in the FCIs for each country, its share in the computation of the index is minor compared to other variables.

As the graphical representation of the FCIs has proven their ability to categorize episodes of financial strain during the last decade, we are now primarily interested in the robustness of results.

5 Usefulness of the FCIs

With the interpretation of results and the high correlation figures between indexes and GDP in mind, we might expect the FCIs to contain substantial leading information on domestic GDP. We do not want to leave this claim uncontested and expose in the following section our FCIs to several robustness tests for further evaluating their usefulness as a policy device. For this reason, and following Gumata et al. (2012) and Lu et al. (2013), the OECD Leading Indicator, together with an autoregressive (AR) GDP model composed only of its own previous values, have been chosen as the main challengers to FCI performance[11].

Hence, we first perform a Granger causality test with the FCIs and the Indicator on whether both indices are able to explain GDP. Thereafter, we assess out-of-sample prediction capability for national GDP for various time horizons ahead of the FCIs compared to a prediction either by the AR model of GDP data or the Leading Indicator. All mentioned exercises are performed for each country in the sample.

5.1 Granger Causality Test

Commencing with the Granger causality test, the table below shows test statistics for both the individual country FCIs and the Leading Indicator. The number of lags tested for is determined via a minimization

[11]The AR GDP series is a natural competitor for GDP forecasting while the OECD Leading Indicator is considered suitable due to a similar complexity in composition in terms of subindexes covered. However, the Leading Indicator exhibits varying components for different countries and cross-country comparability may therefore be rather limited. For instance, the indicator for Brazil contains the index of domestic share prices, domestic production, order books, monetary aggregate M2, discount rate, or net trade with EU.

of information criteria. Test outcomes turn out to be significant at the one percent level and thus reject the null hypothesis H0: *FCI/Leading Indicator does not cause GDP*. Statistics and p-values are stated for all five countries, with India and Russia performing extremely well. As a result, both our FCI and the Leading Indicator have something to say regarding GDP evolvement and may be considered as relevant contestants for further evaluation. Therefore, we further want to figure out underneath which of both indexes performs better for our tasks.

Table 4: Granger Causality Test

Test	Brazil	China	India	Russia	South Africa
FCI does not cause GDP					
Statistic	7.56151	9.31006	19.23431	36.31332	6.98480
p-value	0.00596	0.00227	0.00001	0.00001	0.00822
Leading indicator does not cause GDP					
Statistic	23.42000	6.98371	13.90631	3.07262	23.12981
p-value	0.00001	0.0082	0.00019	0.07962	0.00001

(Source: Authors' calculations)

5.2 Forecast Accuracy

The next paragraphs evaluate the capacity of our indexes as a potential policy tool by assessing their relative performance in forecasting domestic GDP of respective countries in our sample. In fact, the FCI is primarily used to anticipate turning points of business cycles. Following Bernanke (1990), the subsequent equation is estimated:

$$gdp_{t+h} = \phi + \sum_{j=1}^{l} \chi_j gdp_{t+1-j} + \sum_{j=1}^{l} \psi_j index_{t+1-j} + v_t, \tag{4}$$

where *index* represents either our FCI or the Leading Indicator, l is determined by information criteria, and v_t are the residual terms. In the case of ψ_j being significant, both FCI or Leading Indicator combined with the autoregressive part have explanatory power in predicting GDP. For the AR model where only GDP is tested, the *index* term is removed from the equation. The forecast horizon h is set to either 12 or 24 months.

For a comparison of relative predictive accuracy of all three indices we compute mean absolute error (MAE) and root mean square error (RMSE) statistics. MAEs and RMSEs are frequently used risk functions for out-of-sample prediction tests that state the sum of differences between values predicted by model (4) and actually observed growth values. Below, Table 5 states the corresponding MAE and RMSE results from our forecasting exercise. Both measures turn out to be the lowest in the combined series in which the FCI is considered. Overall, the FCI performs better in the long-term forecast than its indicator competitors.

Table 5: MAE & RMSE

	h=12		h=24	
	MAE	RMSE	MAE	RMSE
Brazil				
FCI	**0.973765291**	**1.266546466**	**1.024134361**	**1.311030723**
Leading Indicator	1.025417653	1.408614620	1.082318495	1.453876735
AR Model w/o Ind.	2.865404073	3.713826751	2.720709496	3.42210107
China				
FCI	**4.79867491**	**5.882582003**	**4.844792442**	**5.871247484**
Leading Indicator	4.96063453	6.047617532	5.054904553	6.088422786
AR Model w/o Ind.	5.238036193	6.827795558	6.722673025	8.423722444
India				
FCI	**2.126058842**	**2.822233508**	**2.09323421**	**2.76972717**
Leading Indicator	2.192888736	2.870884287	2.162028939	2.810675958
AR Model w/o Ind.	3.668717422	4.91415989	4.933506003	6.523216444
Russia				
FCI	**1.638555529**	**2.370360085**	**1.724570058**	**2.525209722**
Leading Indicator	1.886990868	2.869814463	2.021306512	2.995901593
AR Model w/o Ind.	5.074246973	11.546216203	9.838379134	35.985079326
South Africa				
FCI	**0.804731162**	**1.341647641**	**0.845945555**	**1.382504426**
Leading Indicator	0.832296029	1.430560761	0.895415102	1.492863218
AR Model w/o Ind.	5.13861091	8.956686556	5.077410975	8.154094585

(Source: Authors' calculations)

5.3 Diebold and Mariano Test

In the following, we assess whether the above yielded differences in MAE and RMSE results with respect to FCI and Leading Indicator are significant. In order to shed light on this question, we run a Diebold and Mariano (DM) test which permits a multiple forecast comparison on the hypothesis of equal expected loss (Diebold and Mariano (1995)). Thus, we first calculate the accuracy of each individual forecast by using a squared error loss function:

$$L(gdp_{t+h}, gdp^i_{t+h|t}) = L(v^i_{t+h|t}) = (v^i_{t+h|t})^2 \tag{5}$$

Second, we test the null hypothesis H0 such that $E(L(v^i_{t+h|t})) = E(L(v^{i+1}_{t+h|t}))$ with the forecast sample $i = 1, 2$ from our exercise. To do so, we compute the test statistic according to the subsequent formula:

$$DM_{statistic} = \frac{\frac{1}{N}\sum_{t=1}^{N}(L(v^i_{t+h|t}) - L(v^{i+1}_{t+h|t}))}{\sqrt{\frac{\hat{f}_h}{N}}}, \tag{6}$$

where N and $\hat{f}$ represent the sample size and the asymptotic variance of $\frac{1}{N}\sum_{t=1}^{N}(L(v^i_{t+h|t}) - L(v^{i+1}_{t+h|t}))$.

The table beneath shows the t-statistics associated twith the DM test.

Table 6: Diebold and Mariano Test

Compared variables	Brazil	China	India	Russia	South Africa
FCI vs Leading	14.87	7.86	9.41	1,88	6.32
FCI vs AR Model w/o Ind.	14.43	8.55	9.52	1,88	6.37
Leading vs AR Model w/o Ind.	4.13	3.46	3.09	6,56	2.44

The numbers stated are the t-stats. (Source: Authors' calculations)
The critical values are in absolute values 1.645 for 10%, 1.96 for 5% and 2.576 for 1%

The positive figures highlight the performance of the FCIs for all sample countries compared to competing series and exhibit significance at the one percent level. Eventually, these results further confirm above stated MAE and RMSE figures and illustrate that our FCIs seem to facilitate the prevision of business cycle turning points.

6 Conclusion

The recent financial crisis has imperatively brought about the need to better monitor developments in domestic and international financial markets as well as potential spillovers to the real economy. This paper aims at such an undertaking by setting up a comprehensive financial conditions index targeted at a broad application to emerging markets, in here epitomized by a BRICS country sample. Subject to data availability, the sample covers a period of January 2001 to March 2013 on a monthly basis.

By employing a rolling-window VAR model, each individual country index delivers estimates of recent effects through the main financial transmission channels on economic activity and sets these impacts into relation to each other. The resulting behaviour of individual indexes reflects their exposure to regional and global crisis events well and is split into common and country-specific components. Whereas the graphs differ due to regional crisis periods up to the eve of 2007-2008, the onset of recent financial turbulences induces very similar negative reverberations. Soon after, however, the likewise rather quickly unreeling recovery process leads over to an again more diverging picture. Global liquidity provision, interest rates or respectively domestic money supply, TED spreads, and the nominal effective exchange rate, all have significant effects on domestic business cycles.

In terms of robustness and forecasting precision, testing our FCIs generally reveals that they trace growth quite well and serve particularly on a longer time horizon as an accurate leading indicator for business cycles. The indexes seem to outperform both the AR Model of the GDP series as well as the benchmark Leading Indicator compiled by the OECD. Our emerging market FCIs may therefore be used as an analytical tool for detecting hostile deteriorations in financial conditions what may prevent potential arrivals of future stress episodes.

The obtained results can further be used for an even more in-depth exploration of financial-macro linkages. Suggested endeavours include a potential integration as an explanatory variable in duration models or the application to a broader sample of countries. Unfortunately, a historic classification and comparison of past events further back in time is hitherto constrained by data availability. However, with the hope of more detailed information to become available soon, this task will be left for future research.

Table 7: Data Sources of Foreign Financial Variables for All Countries

World Production	World Production, Industrial Production excluding Construction, Seasonally Adjusted, Index, 2005=100, Reuters
TED spread	Difference between the LIBOR (United Kingdom Interbank Rates, End of Period, GBP, Central Bank of England) and US Treasury Bills (United States Treasury Bills, Secondary Market T-Bill (Fed), Yield, USD)
Foreign Stock Exchanges	Hong Kong: Hang Seng Index, Price Return, Close, HKD S&P500: Standard & Poor's, USD

Table 8: Domestic Financial Variables for Individual Countries

Brazil (from 1995M01 to 2013M03, sample size = 207)

GDP	Production Approach, Gross Domestic Product, Total, GDP monthly, Current Prices, BRL, Central Bank of Brazil
NEER	Nominal Broad Effective Exchange Rate Index, Average, BRL, BIS
Interest Rate	Immediate Rates (< 24 Hrs), Federal Funds Rate, Total, Federal funds rate, Central Bank of Brazil

China (from 1995M01 to 2013M03, sample size = 207)

GDP	Industry total, growth rate, Chg Y/Y, Central Bank of China
NEER	Nominal Broad Effective Exchange Rate Index, Average, CNY, BIS
Money Supply	M1, CNY, Central Bank of China

India (from 1995M01 to 2012M07, sample size = 199)

GDP	Industrial Production, construction of two series (1993-1994=100 and 2004-2005=100), Central Bank of India
NEER	Nominal Broad Effective Exchange Rate Index, Average, INR, BIS
Money Supply	M1 (EP), INR, Central Bank of India

Russia (from 1996M01 to 2013M03, sample size = 195)

GDP	Total industry excluding construction, Production of total industry, Index, 2005=100, OECD
NEER	Nominal Broad Effective Exchange Rate Index, Average, RUB, BIS
Interest Rate	Immediate Rates (< 24 Hrs), Central Bank Rates, Total, Refinancing rate, OECD
Domestic Stock Exchange	RTS, Index (RTSI), End of Period, USD

South Africa (from 1995M01 to 2012M12, sample size = 204)

GDP	Industrial production, Manufacturing, SA, Index, 2005=100
NEER	Nominal Broad Effective Exchange Rate Index, Average, ZAR, BIS
Interest Rate	Immediate Rates (< 24 Hrs), Central Bank Rates, Total, Discount rate, Central Bank of South Africa

Table 9: Descriptive Statistics (in annual percentage variation)

Country	*Variable*	*Mean*	*STD*	*Med*	*Min*	Max	*Range*
	World production	-0.38	46.36	-0.73	-1.8655	1.05	2.92
	TED spread	0.00	1.51	0.16	5.11	4.28	9.39
	S&P500	5.82	19.39	10.02	-55.35	41.98	97.33
	Hong Kong stock exchange	4.95	27.82	12.21	-80.85	61.70	142.54
Brazil	GDP	10.77	4.84	10.95	-1.15	29.85	31
	NEER	-3.32	16.99	-1.13	-54.28	27.65	81.93
	Interest rate	-2.74	9.06	-1.95	-56.05	21.65	77.70
China	GDP	2.63	6.96	4.38	-21.22	18.98	40.19
	NEER	2.19	5.72	26.77	-9.13	17.63	26.77
	Money supply	1.58	5.25	14.90	3.03	32.90	29.87
India	GDP	6.94	4.79	6.58	-7.24	19.97	27.22
	NEER	-2.37	5.94	-1.50	-17.58	9.55	27.14
	Money supply	0.00	3.52	-0.55	-11.22	11.30	22.52
Russia	GDP	3.04	6.95	4.73	-21.22	18.98	40.19
	NEER	-7.36	18.17	-1.82	-75.44	10.87	86.31
	Interest rate	-5.81	23.21	-2.00	-112	114	226
	Domestic stock exchange	37.09	72.58	26.97	-91.21	362.73	453.94
South Africa	GDP	1.42	5.16	2.45	-22.48	8.90	31.38
	NEER	-4.70	14.45	-5.05	-39.49	30.03	69.52
	Interest rate	-0.54	2.74	-0.50	-0.945	4.85	14.30

(Source: Authors' calculations)

Table 10: ADF Tests

Country	*Variable*	*Lag*	*Value*	*Variable*	*Lag*	*Value*
	World production	p=4	-4.452	TED spread	p=3	-3.821
	S&P500	p=2	1.393	Δ(S&P500)	p=2	-2.736
	Hong Kong stock exchange	p=2	0.887	Δ(Hong Kong stock exchange)	p=2	-3.742
Brazil	GDP	p=5	5.329	Δ(GDP)	p=5	-1.852
	NEER	p=3	-0.832	Δ(NEER)	p=3	-3.537
	Interest rate	p=1	-4.431			
China	GDP	p=3	1.165	Δ(GDP)	p=2	-2.609
	NEER	p=3	1.607	Δ(NEER)	p=2	-2.896
	Money Supply	p=3	6.777	Δ(Money Supply)	p=3	-5.160
India	GDP	p=4	1.806	Δ(GDP)	p=2	-1.794
	NEER	p=3	1.826	Δ(NEER)	p=2	-2.480
	Money Supply	p=3	7.096	Δ(Money Supply)	p=1	-3.185
Russia	GDP	p=3	1.262	Δ(GDP)	p=2	-2.536
	NEER	p=3	1.882	Δ(NEER)	p=2	-2.486
	Interest rate	p=3	-4.774			
	Domestic stock exchange	p=3	-0.652	Δ(Domestic stock exchange)	p=3	-3.341
South Africa	GDP	p=4	1.131	Δ(GDP)	p=2	-2.749
	NEER	p=2	-1.473	Δ(NEER)	p=2	-3.014
	Interest rate	p=4	-4.375			

The numbers are the test statistics. Δ means that data are first differenced.
The critical values at 1%, 5% and 10% are, respectively, -2.652, -1.991 and -1.666.
(Source: Authors' calculations)

Table 11: Correlations

Brazil	Variables	World Production	TED Spread	S&P500	Domestic Production	NEER	Domestic Interest Rate
	World Production	1.0000	0.5303	0.3825	0.1674	0.1824	0.2196
	TED spread	0.5303	1.0000	-0.0571	-0.0100	-0.1217	0.2081
	S&P500	0.3825	-0.0571	1.0000	0.1627	0.2221	-0.0947
	Domestic Production	0.1674	-0.0100	0.1627	1.0000	0.1620	0.1919
	NEER	0.1824	-0.1217	0.2221	0.1620	1.0000	0.1917
	Domestic Interest Rate	0.2196	0.2081	-0.0947	0.1919	0.1917	1.0000
China	Variables	World Production	TED Spread	HK Stock Exchange	Domestic Production	NEER	Money Supply
	World Production	1.0000	-0.1841	0.5846	0.5239	-0.1659	-0.0396
	TED Spread	-0.1841	1.0000	-0.3329	-0.2670	0.0284	-0.2162
	HK Stock Exchange	0.5846	-0.3329	1.0000	0.6131	-0.3433	0.3720
	Domestic Production	0.5239	-0.2670	0.6131	1.0000	-0.6150	0.1920
	NEER	-0.1659	0.0284	-0.3433	-0.6150	1.0000	-0.3280
	Money Supply	-0.0396	-0.2162	0.3720	0.1920	-0.3280	1.0000
India	Variables	World Production	TED Spread	HK Stock Exchange	Domestic Production	NEER	Money Supply
	World Production	1.0000	-0.1925	0.5919	0.4273	0.3333	0.2938
	TED Spread	-0.1925	1.0000	-0.3398	-0.1612	-0.3437	-0.0022
	HK stock exchange	0.5919	-0.3398	1.0000	0.6021	0.4898	0.0067
	Domestic Production	0.4273	-0.1612	0.6021	1.0000	0.3996	0.1923
	NEER	0.3333	-0.3437	0.4898	0.3996	1.0000	-0.1103
	Money Supply	0.2938	-0.0022	0.0067	0.1923	-0.1103	1.0000
Russia	Variables	World Production	TED Spread	Domestic Production	NEER	Domestic Interest Rate	Domestic Stock Exchange
	World Production	1.0000	0.5338	0.3230	0.2980	-0.0812	0.3655
	TED Spread	0.5338	1.0000	-0.1882	-0.1506	0.2896	0.0746
	Domestic Production	0.3230	-0.1882	1.0000	0.2332	-0.1234	0.1827
	NEER	0.2980	-0.1506	0.2332	1.0000	-0.3597	0.5612
	Domestic Interest Rate	-0.0812	0.2896	-0.1234	-0.3597	1.0000	-0.2408
	Domestic Stock Exchnage	0.3655	0.0746	0.1827	0.5612	-0.2408	1.0000
South Africa	Variables	World Production	TED Spread	S&P500	Domestic Production	NEER	Domestic Interest Rate
	World Production	1.0000	0.5286	0.3857	0.5166	-0.1775	0.2578
	TED Spread	0.5286	1.0000	-0.0546	0.0587	-0.3810	0.2530
	S&P500	0.3857	-0.0546	1.0000	0.5473	0.0991	0.1057
	Domestic Production	0.5166	0.0587	0.5473	1.0000	-0.0874	0.1795
	NEER	-0.1775	-0.3810	0.0991	-0.0874	1.0000	-0.2761
	Domestic Interest Rate	0.2578	0.2530	0.1057	0.1795	-0.2761	1.0000

The numbers state the correlations between variables. "HK Stock Exchange" stands for Hong Kong Stock Exchange
(Source: Authors' calculations)

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